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No pixel left behind: Toward integrating Earth Observations for agriculture into the United Nations Sustainable Development Goals framework

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ABSTRACT

Remotely sensed Earth observations (EO) have their history firmly rooted in agricultural monitoring, and more recently with applications in food production, food security, and sustainable agriculture. Still, after more than 45 years of observing the Earth's land surface, usage of EO data by operational monitoring entities concerned with global agriculture is uneven. One reason for this is a gap in continuous communication and collaboration between those who undertake research and development of methods for cropland assessment and monitoring, and those who have the mandate to report on agricultural indicators at a national, regional, and global scales. The recent international policy focus on the United Nations 2030 Agenda for Sustainable Development via its Sustainable Development Goals (SDGs) is giving increased attention to measurements and indicators for monitoring and measuring progress for meeting these goals. Satellite EO provide a source of measurements beyond traditional census data collection and statistical reporting. In this vein, this overview paper describes the current and potential uses of EO data and tools that can support the SDGs, particularly highlighting the activities of the Group on Earth Observations Global Agricultural Monitoring (GEOGLAM) Initiative. GEOGLAM is composed of agricultural ministries, intergovernmental organizations, research entities, universities, space agencies, and members of industry concerned with agricultural monitoring. This GEOGLAM community has a broad portfolio of activities which provide information on the state and changes in agricultural production and land use that can be considered as contributions to both supporting the attainment of several of the 17 SDGs and many of their 169 Targets, as well as monitoring their achievement via the Global Indicator Framework. GEOGLAM contributes in particular to Goal 2: Zero Hunger, but also has less immediately apparent contributions in the realms of water (Goal 6), responsible consumption and production (Goal 12), climate action (Goal 13), life on land (Goal 15), and global partnerships for sustainable development (Goal 17). We further characterize the applicability and use of EO data products and tools as they correspond with the United Nations Interagency Expert Group on Sustainable Development Goals (IAEG-SDGs) Global Indicator Framework. This inventory will be complemented by a discussion of the intersection of other policy mandates with the SDGs in the agriculture and food security contexts, and will conclude with a discussion of approaches to improving awareness of EO value and bridging the gap between policy and EO communities, to the societal benefit of all with no one left behind.

1. Introduction

1.1. Sustainable development, food security, and proliferating policy frameworks

Increasing price volatility in agricultural markets threatens the stability of the global economy as well as food security. Meanwhile, a growing human population with changing consumption patterns and cultivation regimes present pressing challenges to human and natural systems already stressed under a changing climate. These challenges have been recognized by the United Nations through its 2030 Agenda for Sustainable Development (and their associated Sustainable

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Development Goals (SDGs)) (United Nations, 2015a). Predating the SDGs were the Millennium Development Goals (MDGs), which were agreed upon by governments in 2000 and expired in 2016. The MDGs set out to address growing social stratification, epidemic poverty, and public health in member states (Sachs, 2005; United Nations, 2009), but failed to recognize the inherent value of geospatial data, limiting their ability to evaluate progress (Scott and Rajabifard, 2017). In designing the SDGs, member countries called for better communication among member states and development practitioners, the incorporation of processes to ease monitoring and reporting burdens, and the bringing of member state priorities to the foreground (Griggs et al., 2013). Further, the final MDG report explicitly stated, “comprehensive location-based information is helping Governments to develop strategic priorities, make decisions, and measure and monitor outcomes”, demonstrating clear inroads for remotely sensed EO and the geospatial information that it can create (United Nations, 2015b).

The need for action around food security and agriculture has also been recognized by the Group of 20 (G20). In 2011, the G20 Agricultural Ministers requested a proposal on agricultural monitoring in the context of their action plan to reduce price volatility through bringing transparency to agricultural markets. The Group on Earth Observations (GEO) Agricultural Monitoring Community of Practice – organized beginning in 2007 with a community agenda and priorities identified (Becker-Reshef et al., 2009; Justice and Becker-Reshef, 2007) – created a proposal for a GEO Global Agricultural Monitoring (GEOGLAM) Initiative to enhance the international community's capacity to utilize Earth observations to produce and distribute timely, accurate, reliable, and actionable information on food production for both stabilizing markets and providing early warnings of food shortages (G20 Agricultural Ministers, 2011; Singh Parihar et al., 2012). GEOGLAM was endorsed along with the Agricultural Market Information System (AMIS), which brings together countries responsible for the majority of production of agricultural commodities and provides a forum for coordinating policy action to prevent market uncertainty (Brockhaus and Kalkuhl, 2014; Spratt, 2013). The two initiatives were encouraged to work together and the Crop Monitor was developed by GEOGLAM as an input to the AMIS Market Monitor (Anderson et al., 2017; Becker-Reshef et al., 2013; Fritz et al., 2018; van der Velde et al., 2018). GEOGLAM is a voluntary, best-efforts initiative, made up of over 130 national and international agencies (as of 2018) concerned with agricultural monitoring, including space agencies, ministries of agriculture, research organizations, universities, and private industry. GEOGLAM represents a diversity of crop and rangeland management systems as well as mandates and priorities, but with a common thread: the use of satellite EO for monitoring agricultural production and land use, including rangelands through its Rangeland and Pasture Productivity Initiative (RAPP; www.geo-rapp.org).

In addition to these two current frameworks, there are hundreds of national and multi-lateral commitments and agreements addressing environmental sustainability and social and economic development, each with its attending monitoring and evaluation schemes, cutting across scales, actors, and domains (Reyers et al., 2017). In short, the global sustainability policy landscape as relevant to agriculture and food security is vast, and synergies across reporting requirements and actors has not yet been optimized. Further, geospatial data in general and remotely sensed Earth observations (EO) in particular have not been included as relevant data sources for monitoring and evaluation. The potential and current place of Earth observations (EO)-based agricultural monitoring within this policy landscape merits inspection so as to maximize the value of existing investments and minimize reporting burden by responsible agencies.

1.2. Earth Observations for agriculture: technological expansion and remaining gaps

Although satellite observations of land began with agricultural monitoring (Doraiswamy et al., 1979; Kleweno and Miller, 1981; MacDonald et al., 1975; Pinter et al., 2003; Pitts and Badhwar, 1980), only in recent years has agricultural remote sensing seen reinvigoration as space agencies, national ministries of agriculture, and global initiatives have refocused research and operationalization efforts on utilizing satellite data for monitoring agriculture (as discussed in, e.g., Atzberger (2013); Fritz et al. (2018); Whitcraft et al. (2015a)). This reinvigoration has been driven by the increasing need for solutions to hunger, unsustainable land use and the impact of climate change, but has been facilitated by key shifts in data policy (“free and open access to global data,” e.g. NASA/USGS-Landsat, NASA-MODIS, European Commission-Copernicus), computation infrastructures and analytics (“the Cloud,” “internet of things,” cellular data access), and data availability (public sector investments as well as private sector entry into the Earth observation sector) (Azzari and Lobell, 2017; Belward and Skøien, 2015; Claverie et al., 2018; Giuliani et al., 2017; Nativi et al., 2015; Wulder et al., 2015), as well as through GEOGLAM efforts to advance the state of the science and use of EO data for agricultural assessment.

The whole Earth is observed at least once daily, these data are made available in near-real time, and cloud-based computing systems are only now catching up to the deluge of open data that has been made freely available in recent years. Provided all launches are successful, in 2020, we will have freely-and-openly available images of the agricultural Earth in the visible through shortwave infrared every 2–4 days at < 30 m (Landsat 8–9, Sentinel 2a, b, c), as well as 10–20 m dual polarization C-band synthetic aperture radar every 2–4 days (Whitcraft et al., 2015c). This will provide the agricultural monitoring community with data of sufficient spectral, spatial, and temporal resolution to monitor critical variables and derive key products including cropland and rangeland masks, crop type map and planted area, cropland and rangeland condition, crop yield forecast, water use and productivity, field delineation, crop phenology/stage, and crop biophysical variables (biomass, leaf area index, photosynthetically active radiation, fractional cover, and height), and related environmental variables (evapotranspiration, land surface temperature, soil moisture) (Whitcraft et al., 2015a, 2015b; 2015c, 2018a, Table 1). Meanwhile, there are community efforts – within GEOGLAM and together with the Committee on Earth Observations Satellites (CEOS) as well as their constituent civil space agencies – to ensure consistent pre-processing, validation, and distribution/accessibility of these critical EO datasets and their derived products (Dwyer et al., 2018; Giuliani et al., 2017; Helder et al., 2018; Lewis et al., 2018; Lynnes et al., 2017).

These derived products have already found use within several national and international monitoring agencies for crop condition assessment, yield forecasting and assessment, area estimation, and early warning of crop failures (e.g. USDA Foreign Agricultural Service (Crutchfield, 2016), China CropWatch, (Wu et al., 2013), GEOGLAM Crop Monitor (Becker-Reshef et al., in review, submitted), European Joint Research Centre Monitoring Agriculture with Remote Sensing (Baruth et al., 2008), USDA NASS (Johnson, 2014; Johnson and Mueller, 2010), and the Famine Early Warning Systems Network (Funk et al., 2019); see review articles by Atzberger (2013) and Fritz et al. (2018)). These data have been used together with economic data to create policy-relevant information in the realms of domestic and international food policy, food prices, and food aid (Becker-Reshef et al., 2016, 2018; Becker-Reshef et al., 2018; Oliva et al., 2016).

However, despite these evident impacts, clear policy drivers (in particular the G20 Action Plan), and technological advances with respect to quality, quantity, and availability of EO data, there remain critical gaps in EO adoption. Some countries use little to no satellite-based information in their agricultural assessments, and global policy drivers – including the primary focus in this article, the UN SDGs – generally leave EO data out of their indicator methodologies. The question then remains: *if there has been such a proliferation of the data itself, the systems for its quality assessment and control, and the platforms for accessing and utilizing the data, and the methods for deriving meaningful*

Table 1

A table of GEOGLAM satellite data (right columns) requirements for community information needs ("target products" along top row), updated in 2018 in response to multiple sources including community survey, workshops, literature review, and research site information (Whitcraft et al., 2018a). This built upon the methods and efforts described in Whitcraft et al. (2015a). Requirements are characterized by spatial & spectral range, frequency with which reasonably cloud-free data are required, geographic extent of satellite acquisition, as well as the target product for which the measurements are suitable. Specific target product requirements are further refined by the field sizes for which a certain measurement would be useful. These appear on the right side of the table, where "L" refers to "Large fields" (defined as > 15 ha), "M" refers to "Medium fields" (defined as 1.5–15 ha), and "S" refers to "small fields" (< 1.5 ha). The symbol "x" indicates that these data are useful for that product's generation for all field sizes. "VIS" indicates spectral coverage in the visible range (wavelength = ~400–700 nm), "Red Edge" indicates the same for ~680–750 nm, NIR is "near infrared" (~750–1300 nm), SWIR is "shortwave infrared" (~1300–3000 nm), thermal is "thermal infrared" (~3000–14000 nm), passive microwave (frequency = 1–200 GHz; wavelength = 0.15–30 cm), and SAR is "synthetic aperture radar" with multiple frequencies in the 1–5.5 GHz range (3–25 cm wavelength).

					Core Information Products and Essential Agricultural Variables for GEOGLAM											
					Within Season Crop Mask	Within Season Crop Type Mask	Crop (Type) Area Indicator	Crop Condition Indicators	Current Crop Phenology & Ag Practices	Biomass, LAI, fAPAR, fCover, NDVI, Height	Within Season Yield Forecast	End of Season Yield Estimation	Soil Moisture	ET, Water Use, Water Productivity LST	Usual Crop Calendars	Field delineation
Target Product Update Frequency:					Monthly	Monthly	Mid of Season	Weekly	Weekly	Weekly	Monthly	End of Season	Daily	Daily	Every 5 years	Every 3 years
Coarse Resolution Sampling (> 30 m)																
1	100–1000 m	optical	Twice daily	Wall-to-Wall				X		L	L	L			L	
2	50–500 m	optical	2-5 per week	Cropland extent	X	X		X	L	L	L	L		X	L	
3	5–25 km	passive microwave	Daily	Wall-to-Wall				X		X	X	X	X	X		
4	30–100 m	thermal	2 to 7 per week	Cropland extent		X		X		X	X	X	X	X		
Moderate Resolution Sampling (10 to 30 m)																
5	10–30 m	VIS NIR + Red Edge + SWIR	Weekly	Cropland Extent	X	X		X	X	X	X	X		X	X	L
6	10–30 m	SAR dual polarization	2-4 per week	Cropland extent	X	X	L		X	X	X	X	X	X	X	L
7	10–30 m	SAR coherence	2-4 per week	Cropland extent	X	X	L		X	X	X	X	X	X	X	L
8	10–30 m	SAR Multifrequency	Weekly	Cropland extent	X	X	X		X				X		X	
Fine Resolution Sampling (5 to 10 m)																
9	5–10 m	VIS NIR + Red Edge + SWIR	Weekly	Cropland Extent	X	X	X	X	X	X	X	X		X		L
10	5–10 m	SAR dual polarization	2-4 per week	Cropland extent (cloudy & rice)	M/S	M/S	X		M/S	X			X	X		
Very Fine Resolution Sampling (< 5 m)																
11	< 5 m	VIS NIR	3/year (2 in +1 out of season)	Cropland extent of small fields, every 3 years	S	S	M/S									M/S
12	< 5 m	VIS NIR	1 to 2/3 years	Cropland extent												M/S
13	< 3 m	VIS NIR	1 to 2 per month	Refined Sample of All Fields	S	S	X				X	X				M/S
14	< 5m	SAR Multifrequency	Weekly	Cropland extent (cloudy)					X	X			X			

information, why does there remain uneven adoption of satellite-based Earth observations data for agricultural monitoring?

This article aims to address this question, and further accomplish five things: first and second, to characterize the ways in which Earth observations in general and GEOGLAM's activities in particular are supportive to the UN SDGs, both with respect to (first) *attaining* the targets and Goals, as well to (second) *monitoring* variables that are relevant indicators of progress toward the targets and Goals; third, to characterize applicability of satellite data products, tools, and methods for indicators, in the process introducing the GEOGLAM community effort toward defining "Essential Agricultural Variables for GEOGLAM"; fourth, to identify synergies and intersections between proliferating national, bilateral, and multilateral policy mandates and information needs, particularly where EO data can be useful; and fifth, to unpack the above question and in the process, provide insight into overcoming communication challenges and capacity gaps relative to the perceived and actual utility of EO to the economics, statistical, and policy communities.

2. Earth observations for agriculture & the UN SDGs: contributions of GEOGLAM & the broader EO community

Since GEOGLAM's 2011 launch, it has implemented a variety of activities, including regional networks (e.g. Asia-RiCE, AfriGAM, and GEOGLAM Latinoamérica (Ryan, 2017; Takashima et al., 2013; Whitcraft et al., 2018b)), a variety of research and development activities drawn together through the Joint Experiment in Crop Assessment and Monitoring (JECAM) (Bontemps et al., 2015b; Bydekerke et al., 2015; Oyoshi et al., 2016), and a working group geared at coordinating best practices for individual and institutional capacity development (GEOGLAM Executive Committee, 2019). In addition, a strong connection was made between GEOGLAM and the Committee on Earth Observation Satellites (composed of the world's space agencies) to represent and advocate for the observation requirements from the agriculture community (Whitcraft et al., 2015c). With a clear statement of priority monitoring needs from operational users, a program of operational research and development is being promoted to deliver new monitoring capabilities and information.

2.1. Attaining the Sustainable Development Goals and their targets

GEOGLAM activities have been focused on fulfilling the G20 policy mandate, and have in the process found success, as evidenced by the G20 Agricultural Ministers' 2018 Declaration, recognizing GEOGLAM "amongst the key mechanisms to promote transparent markets and food security" (G20 Agricultural Ministers, 2018). These efforts are nevertheless contributing to the attainment of multiple Sustainable Development Goals as well as targets, which are summarized in Table 2 (with all material in the "Goal or Target" column drawn from the UN SDG Knowledge Platform Website (United Nations, 2018)). These efforts could be further levered as GEOGLAM is the only intergovernmental, inter-agency community focused on EO for agriculture with the critical mass to work both at the UN-level (where methodologies are defined; see Section 2.2) as well as at the national level (where SDG implementation/reporting will take place). This overlapping value of efforts is essential and in fact practically mandated by the final report of the Millennium Development Goals, which stated, "once the geospatial data are created, they can be used many times to support a multiplicity of applications" (United Nations, 2015b).

The final goal of the UN SDGs – Goal 17 – is to, "strengthen the means of implementation and revitalize the global partnership for sustainable development," with multiple targets focusing on capacity development, south-south, north-south, and triangular international cooperation, and to improve provision of high-quality, timely, and reliable data disaggregated by geographic location (targets 17.6, 17.9, and 17.18). All of these targets are at the core of GEOGLAM's G20 mandate as well as its evolving efforts.

2.2. Monitoring progress toward achieving the UN SDGs: the Global Indicator Framework

When the UN SDGs were announced in 2015, the UN Statistical Commission charged the Inter-agency Expert Group on Sustainable Development Goal Indicators (IAEG-SDGs) with developing a set of global, quantitative indicators by which *national* statistical offices (NSOs) and other national government departments and agencies could (eventually) monitor and report upward their progress toward achieving the SDGs (Adams and Judd, 2016). In 2017, the UN Statistical Commission endorsed an initial set of 230 indicators associated with the 169 targets under the 17 Goals. As of early 2018, there are 37 additional indicators under review for 14 Goals (Adams and Judd, 2018). The SDGs are member state-led and implemented, and this national-level focus of the "Global Indicator Framework" was touted as a key lesson-learned from prior UN development efforts (e.g. the Millennium Development Goals (MDGs); Scott and Rajabifard (2017); United Nations (2015b); United Nations General Assembly (2015)). Still, acknowledging the complexity of gathering data disaggregated by gender, age, income, geography, and occupation, each indicator has been assigned a Custodian Agency which helps develop methodologies and assists countries with gathering, analyzing, and reporting data upward to the IAEG-SDGs (UN FAO, 2017).

Like the MDGs before them, these indicators are largely based on statistical data, although the IAEG-SDGs has a growing recognition – thanks to the intervention of entities like the Group on Earth Observations (GEO) and the UN Expert Committee on Global Geospatial Information Management (UN-GGIM) – of the value of geospatial information in disaggregated monitoring and in addressing issues from sub-national to global scale (Scott and Rajabifard, 2017). Further, the IAEG-SDGs has articulated that data should be policy-relevant and "not exist for its own sake" (Adams and Judd, 2018), highlighting that different countries may have existing data collection and reporting regimes for their other policy mandates and therefore efforts should be made to accommodate and harmonize those data for global progress reporting. As characterized in Table 2 and 3, there exist many methods, data sets, and operational systems implementing EO for activities suitable to supporting the SDGs, and as such it is to the benefit of the broader community to maximize their utility by incorporating them into new reporting requirements, such as the SDGs.

Many indicators have primary data sources as well as secondary data sources (often including geospatial and EO data) associated with their production. Toward promoting the inclusion of EO-based indicators and sub-indicators, interaction to-date between the EO community and the IAEG-SDGs and Custodian Agencies has occurred on an ad hoc basis. Consequently, GEO and in particular the "EO4SDG" initiative has a challenging and potentially key role in helping to make the connections between the EO community and the custodial agencies within the national and global statistical institutions (Anderson et al., 2017).

2.2.1. Contributions of GEOGLAM quantitative monitoring to SDG indicators

In addition to the ways in which GEOGLAM's activities contribute to meeting the goals and targets articulated in Section 2.1, so too are a number of GEOGLAM activities aligned with the indicators which have been articulated by the United Nations to monitor progress toward their achievement. However, as opposed to the case of goals and targets themselves, the contributions of GEOGLAM activities to monitoring progress toward meeting them vis-à-vis the indicators is neither implicit nor automatic. Rather, in order for GEOGLAM activities to meaningfully contribute in this way, several complementary and iterative activities must take place:

Table 2
A mapping of 2030 Agenda for Sustainable Development Goals and Targets to examples of GEOGLAM and EO data contributions.

Goal or *Target*	Description of Intersection(s) between SDGs, GEOGLAM, EO, and/or agriculture.	Example GEOGLAM & EO Contributions
Goal 1: End poverty in all forms everywhere. *Target 1.5: By 2030, build the resilience of the poor and those in vulnerable situations and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters.*	More than 30% of the world population's livelihood is drawn from agriculture (FAOSTAT, 2012). Satellite data provide synoptic early warning of climate-related and extreme events, allowing for multi-scalar adaptive and/or mitigative measures in agrarian settings. This can support resilience.	The Office of the Prime Minister in Uganda now utilizes satellite data (in particular, NDVI anomaly coupled with agroclimatic indicators) as their primary trigger for their own disaster risk financing fund. This fund enables farmers to purchase seeds for a new season, and to reinvest their labor in local infrastructure development. Satellite data allow them to react earlier and spend less than in previous years, with the Commissioner of the Office of the Prime Minister of Uganda explicitly stating, "In the past we always reacted to crop failure, spending billions of shillings to provide food aid in the region. 2017 was the first time we acted proactively because we had clear evidence from satellite data very early in the season (Owor, 2018)."
Goal 2: End hunger, achieve food security and improved nutrition and promote sustainable agriculture.	Food security is at the core of GEOGLAM's G20 policy mandate.	EO data improve the availability and timeliness of information on crop failures and production shortfalls from farm to global scales, empowering decisions related to food security, from global food aid to (re)insurance activation to farmer response.
Target 2.a: Increase investment, including through enhanced international cooperation, in rural infrastructure, agricultural research and extension services, technology development and plant and livestock gene banks in order to enhance agricultural productive capacity in developing countries, in particular least developed countries.	"Agricultural research and extension services" typically refer to on-farm technology to maximize yield and minimize environmental impact, but in fact must include off-farm technology as well. This includes monitoring technology which can provide key insight into monitoring and evaluating agricultural interventions at farm to national to global scales.	GEOGLAM maintains an international agricultural research site network known as JECAM (Joint Experiment on Crop Assessment and Monitoring) which aims to develop monitoring and reporting protocols as well as 'best-practices' for monitoring agricultural indicators in diverse systems across the globe (Bontemps et al., 2015a; Jarvis et al., 2016). JECAM is composed of over 40 sites across the globe, of which approximately half are in developing countries. (www.jecam.org). GEOGLAM also works to transition research to operations. In Argentina, participant Instituto Nacional de Tecnologia Agropecuaria (INTA) developed a satellite-based indicator of agricultural drought impact (actual evapotranspiration anomaly, following Di Bella et al. (2000), and crop type mapping (King et al., 2017; Song et al., 2017)) that the Ministry of Agroindustry used to declare a state of emergency for farmers in 27 municipalities (" Buenos Aires: declararon la emergencia por sequía para 27 municipios - LA NACION," 2018). In Brazil, Conab (Brazil's National Supply Company, linked to the Ministry of Agriculture) has operationally implemented the MODIS and VIIRS-based Global Agricultural Monitoring System for condition monitoring (Becker-Reshef et al., 2009) as well as a satellite-based method for sample-based crop area estimation resulting from a decade-long relationship with actors in the GEOGLAM community of practice (Conab and INMET, 2019; Fernandes et al., 2019; Song et al., 2017; Zalles et al., 2019).
Target 2.c: Adopt measures to ensure the proper functioning of food commodity markets and their derivatives and facilitate timely access to market information, including on food reserves, in order to help limit extreme food price volatility	In a report to the G20 on Food Price Volatility that recommended the creation of AMIS, it was noted that, "a lack of reliable and up-to-date information on crop supply … contributed to recent price volatility (FAO, 2011, p. 18)." Given that commodity crop cultivation for production and export are concentrated geographically (with the top 5 producers of rice and maize contributing to 70% of global production and 80% of global exports, respectively), a spatially explicit, sub-national, and timely understanding of crop conditions as they impact production is critical (Tadasse et al., 2016).	GEOGLAM has since 2013 operationally produced the Crop Monitor as input to the AMIS Market Monitor, the main monthly product of AMIS (Becker-Reshef et al., in review; Fritz et al., 2018). The CM4AMIS is a monthly consensus bulletin on crop conditions and outlooks on production, generated through combining satellite data, agrometeorological data, and expert opinion from over 40 institutes worldwide (www.cropmonitor.org). EO and their integration with multi-annual forecasting and condition models can provide earlier indications of supply shocks. Quantifying the impact of market information systems in general (and by extension AMIS itself) on food prices and their volatility is methodologically difficult (FAO, 2017; Staatz et al., 2014), although models and theory bear out the connection between supply information transparency and mitigated price shocks (Brockhaus and Kalkuhl, 2014; Brooks, 2014; Tadasse et al., 2016) and some have attributed reduced market instability since 2011 to AMIS and its Market Monitor (da Silva, 2013).

(*continued on next page*)

Table 2 (*continued*)

Goal or *Target*	Description of Intersection(s) between SDGs, GEOGLAM, EO, and/or agriculture.	Example GEOGLAM & EO Contributions
Target 2.1: By 2030, end hunger and ensure access by all people, in particular the poor and people in vulnerable situations, including infants, to safe, nutritious and sufficient food all year round.	One of the pillars of food security is availability, which agricultural production directly impacts (Barrett, 2010). Early warnings of crop shortfalls or failures, which EO provides, can allow local, national, and global action to promote human access to food (FAO, 2017).	GEOGLAM has since 2016 operationally produced the Crop Monitor for Early Warning (CM4EW), an analog to the Crop Monitor for AMIS, which pulls together several agencies concerned with early warning and food security to produce monthly, transparent, consensus reports on crop conditions in countries most at risk of food insecurity (Becker-Reshef et al., submitted; Rembold et al., 2018). Examples of impact of the CM4EW on food security decisions are given in Section 2.2.2.
Target 2.4: By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality.	Satellite data have been used to both establish a baseline of what currently exists (current practices, current production levels, current land use and land cover (Atzberger, 2013; Fritz et al., 2018)), as well as measure the implementation and efficacy of agricultural land use interventions aimed toward improving land and soil quality while maintaining or increasing agricultural production (Lobell, 2013; Lobell et al., 2002; Mattia et al., 2017, 2017; Van Lynden and Mantel, 2001; Zaussinger et al., 2019).	GEOGLAM is coordinating international research and development activities which can elucidate pathways toward long-term sustainable agriculture. These R&D efforts – through initiatives like JECAM, SIGMA, Sentinel-2 for Agriculture, and Asia-RiCE (Bontemps et al., 2015b; Gilliams and Bydekerke, 2014; Jarvis et al., 2016; Takashima et al., 2013) – are enhancing capacity to assess interannual variability in cultivation practices and their impacts on cropland productivity and on the environment.
Goal 6: Ensure availability and sustainable management of water and sanitation for all. *Target 6.4: By 2030, substantially increase water-use efficiency across all sectors and ensure sustainable withdrawals and supply of freshwater to address water scarcity.* *Target 6.5: By 2030, implement integrated water resources management at all levels, including through transboundary cooperation as appropriate.*	Agriculture utilizes on average two-thirds of accessible freshwater on Earth (Clay, 2004). Further, 70% of global water freshwater withdrawal is for irrigation (Foley et al., 2011). And additionally impacts water resources via land degradation, changes in runoff, and unsustainable use of ground water (Alauddin and Quiggin, 2008).	Earth observations can help monitor rainfall (Funk et al., 2015), forecast drought (Jayanthi et al., 2014; Shukla et al., 2014), water requirement satisfaction (McNally et al., 2015), water use efficiency (Blatchford et al., 2018; Wu et al., 2015), and the state of water supplies for food security implications (McNally et al., 2019, 2017). Additionally, through precision management, EO can help optimize on-farm decisions related to water use (Khanal et al., 2017; Liaghat and Balasundram, 2010).
Goal 12: Ensure sustainable consumption and production patterns.	Understanding the potential magnitude of different patterns of production requires an understanding of current and historical practices, which EO can help provide. Then, as changes to land management occur, EO can provide continuous monitoring.	GEOGLAM partners are engaged in the monitoring of agricultural practices, including water use, cropping cycles, tillage, and crop residue (Daughtry et al., 2005; McCarty et al., 2009; Pinter et al., 2003).
Target 12.A: Support developing countries to strengthen their scientific and technological capacity to move towards more sustainable patterns of consumption and production. ***Related:*** *Target 3.D: Strengthen the capacity of all countries, in particular developing countries, for early warning, risk reduction and management of national and global health risks.*	In the SDG indicator framework, national statistical offices (NSOs) are responsible for monitoring and reporting their progress toward achieving goals (Adams and Judd, 2016). Scientific and technical capacity to monitor for early warning of food insecurity with EO will support this activity.	GEOGLAM has a dedicated working area to Capacity Development for EO-based Agricultural Monitoring, with the end of goal of enhanced national capacity to monitor their own resources. This is implemented through regional networks (e.g. Asia-RiCE (www.asia-rice.org), AfriGAM, and Agricultural Monitoring in the Americas (www.agamericas.org), which emphasize South-South knowledge and technology transfer. These activities range from short-term workshops and webinars to medium-term institutional exchange, to long-term relationships between institutions, all toward strengthening scientific capacity to monitor agriculture and support sustainable development. National implementations of the Crop Monitor – for example, in Uganda, Tanzania, Kenya, and Vietnam (Justice, 2019) – have been particularly valuable in managing risks to food security and in turn human health.
Goal 13: Take urgent action to combat climate change and its impacts. *Target 13.3: Improve education, awareness-raising and human and institutional capacity on climate change mitigation, adaptation, impact reduction and early warning.*	The agricultural sector is responsible for roughly 24% of global greenhouse gas emissions, before accounting for offsets via soil and biomass carbon sequestration (Pachauri et al., 2014; Tubiello et al., 2014). Increasing agricultural resilience and strengthening food security are critical parts of mitigating the impacts of climate change, on both the environment and on human livelihoods. Early warnings of crop shortfalls can help.	Highlighting the *trans*-sectoral and interdisciplinary nature of climate change, GEOGLAM's contributions to achieving Target 13.3 – principally through capacity development and through the Crop Monitors for AMIS and Early Warning – have been introduced under multiple other targets and goals. The Crop Monitor additionally includes a within-season tracking of El Nino events and their potential impacts on crop production worldwide.
Goal 15: Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss *Target 15.3: By 2030, combat desertification, and restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land-degradation neutral world.*	Rangelands and pastures cover approximately one third of the world's land area and as global meat consumption increases, there is increased pressure on grazing lands worldwide (Guerschman et al., 2015). Sustainable agricultural and rangeland management practices are essential to progressing toward land degradation neutrality.	Combining RAPP community information on spatially explicit biomass, vegetation condition information, and vegetation fractional cover (Guerschman and Hill, 2018) with national an animal herd statistics empowers forecasting of meat production (with food security impacts, cutting across multiple SDGs), risks of land degradation, and emissions from ruminants. The Group on Earth Observations has recently launched a "Land Degradation Neutrality" Initiative, which aims to empower local and national actors use of EO for planning action to work toward a land-degradation neutral world (Anderson et al., 2017)

1. Identify the indicators and associated sub-indicators which have agricultural components with measurable biophysical quantitie-s;order
2. Identify the current and "adjacent" GEOGLAM activities which align with these indicators and associated sub-indicators;order
3. Define the value proposition of utilizing EO-based spatial

Table 3
The relevance and current use of Earth observations within the existing Global Indicator Framework (with Indicator, Custodian Agency, and Tier as of October 2018 (IAEG-SDGs, 2018a)).

Indicator	Custodian Agency	Tier as of Oct 2018 (See Appendix)	Current or Proposed Use of RS in Official Methodology	Potential Use of EO & GEOGLAM Activities
2.3.1: Volume of production per labour unit by classes of farming/pastoral/forestry enterprise size	FAO	II	None	EO can be used to delineate field boundaries (Fritz et al., 2018; White and Roy, 2015; Yan and Roy, 2016) and help determine enterprise size. EO can also be used for spatially explicit yield, area, and therefore production estimation (Becker-Reshef et al., 2018; Franch et al., 2015; Gallego et al., 2010; Johnson, 2014). These are all articulated GEOGLAM community requirements (Table 1). In fact, Agriculture and Agrifood Canada developed an in-season crop yield forecaster model that integrates EO, which Statistics Canada now operationally implements in place of their historic and expensive end-of-season September survey (Chipanshi et al., 2015; Statistics Canada, 2018, 2015)
2.4.1: Proportion of Agricultural Area Under Productive and Sustainable Agriculture	FAO Partner: UNEP	III	Listed as alternative option	EO-based information is explicitly identified as an "alternative data source" for a variety of its sub-indicators, including farm output value per hectare (e.g. via crop mapping and area estimation), prevalence of soil degradation, variation in water availability, management of fertilizers, and use of biodiversity-supportive practices (e.g. tillage mapping, cover crop monitoring, and crop residue monitoring). See full discussion in Section 2.2.2.
6.4.1: Change in water-use efficiency over time	FAO Partners: UNEP, IUCN, UNSD, OECD, Eurostat	II	None	While the IAEG-SDGs method characterizes water use efficiency (WUE) in economical terms, WUE also has an agronomic meaning of crop yield per unit of water use (Howell, 2001) and satellite data have demonstrated use in monitoring water use and water productivity (Anderson et al., 2012). EO-based methods for irrigation mapping, water withdrawal quantification, water productivity and management assessment, and measurements of water use efficiency are improving (Brocca et al., 2018; Löw et al., 2017; Schollaert Uz et al., 2019; Wu et al., 2015; Zaussinger et al., 2019).
6.4.2: Level of water stress: freshwater withdrawal as a proportion of available freshwater resources	FAO Partners:UNEP, IUCN, UNSD, EOCD, Eurostat	I	None	EO can be used to objectively identify surface water, irrespective of its political ownership (García et al., 2016; McFeeters, 1996; Mueller et al., 2016). Within GEOGLAM, monitoring of water use in agricultural systems is prioritized (Table 1), the monitoring of which can help identify withdrawals and help national government monitor (shared) water resources (van Niekerk et al., 2018).
6.5.2: Proportion of transboundary basin area with an operational arrangement for water cooperation	UNESCO-IHP, UNECE	II	None, although geographic information system (GIS) usage for spatial analysis is noted.	
15.3.1: Proportion of land that is degraded over total land area	UNCCD Partners:FAO, UNEP	II	"Regional and global datasets derived from Earth observation … can play and important role in the absence of, to complement, or to enhance national official data sources (15.3.1 Metadata (IAEG-SDGs, 2018b)).“3 Sub Indicators: Trends in Land Cover (degraded area)- Land Productivity (net primary productivity)- Carbon stocks (soil organic carbon)	EO for land cover change (Bontemps et al., 2013; Hansen et al., 2013; Hansen and Loveland, 2012; Townshend et al., 1991), land productivity monitoring (Field et al., 1995; Jackson and Prince, 2016; Reeves and Baggett, 2014; Ruimy et al., 1994; Turner et al., 2006; Zhao et al., 2005), and carbon stock monitoring (Avitabile et al., 2016; Goetz and Dubayah, 2011) using EO are well-established, although the primary metric used for carbon stocks is soil organic carbon, for which EO-based methods are less mature (Duncanson et al., 2019). IAEG-SDGs stated concerns about the need for development of national capacity to process, interpret, and validate the higher volumes of fine resolution satellite data (in 15.3.1 Metadata (IAEG-SDGs, 2018b)) is a key avenue through which GEOGLAM and associates (e.g. CEOS) can assist, given their recent focus on computational infrastructures for spatial data management (GEOGLAM Executive Committee, 2019; Lewis et al., 2017, 2016). .

information in place of or in complementarity with non-EO-based information;order
4. Work with UN Custodian Agencies and/or directly with the NSOs and NMAs to pilot the use of EO methodologies;order
5. Refine the methodological best-practices and *in situ* and satellite data requirements for deriving the necessary metrics.order

To assist particularly in items 1, 2, and 3 above, in Table 3 we present a mapping of existing IAEG-SDG indicators to GEOGLAM and related activities, including a characterization of both the status of the indicator in the UN system and its inclusion/exclusion of satellite-based EO, as well as the potential use for satellite-based EO. This was compiled through a thorough review of the existing indicators and sub-indicators (IAEG-SDGs, 2018a). This was done specifically in the GEOGLAM context; there are other uses of EO that are beyond agricultural monitoring and beyond GEOGLAM's purview. Then, because several indicators as articulated leave little if any room for the inclusion of geospatial metrics and information, but geospatial data and specifically EO could be used to measure progress toward a target, we propose alternative or complementary EO-based indicators or sub-indicators for consideration for the related targets.

2.2.2. Alternative data sources and alternative indicators

For some Indicators, EO data are not even mentioned in the IAEG-SDGs metadata documentation but could nevertheless be useful. This is the case for indicator 2.1.2, Prevalence of moderate or severe food insecurity in the population, based on the Food Insecurity Experience Scale (FIES; FAO, Tier II), which also appears as a sub-indicator for Indicator 2.4.1. The FIES is a short, face-to-face questionnaire that according to the UN has the benefit of being quick and easy to administer at limited cost (2.1.2 Metadata (IAEG-SDGs, 2018c)). However, the replicability and latency of such a survey particularly in times of crisis and acute food insecurity is of concern. The integration of EO-based early warning information – such as that tracked on a monthly basis by the Crop Monitor for Early Warning (Becker-Reshef et al., submitted) – could highlight regions experiencing biophysical risk-factors (e.g. anomalous temperatures, anomalous rainfall sum, vegetation condition anomalies, delayed planting) and sociopolitical risk-factors (e.g. conflict). By utilizing this low-latency, regular, consensus-based, sub-national resolution, global-scale evaluation of the crop conditions, countries and international humanitarian groups alike can focus limited evaluation and response resources on areas most likely to be impacted by acute and localized food insecurity. In fact, there have already been examples where the CM4EW have been used to direct international focus for action and deeper analysis to regions experiencing conditions which place people at risk of acute food insecurity. For example, in February 2018 the UN Office for Coordination of Humanitarian Affairs issued a “special alert” calling for urgent action in Southern Africa based in part on EO-based conditions reported through the Crop Monitor (UN OCHA, 2018). In another example, USAID drew upon the CM4EW's within-season, continuous monitoring of continental-scale, subnational-level crop conditions to direct international humanitarian attention toward areas of significant concern in Eastern Africa and Yemen (USAID Agrilinks, 2019). As EO-based monitoring becomes entrenched in food security and disaster monitoring, it makes sense to capitalize on those resources for other mandated reporting and monitoring (such as the UN SDGs) as well.

A similar case can be made for indicator 6.4.1, Change in water use efficiency over time (FAO, Tier II), for which “water use efficiency” (WUE) is described in strictly economic terms, as value per unit volume (Metadata, 6.4.1(IAEG-SDGs, 2018d),). Meanwhile, WUE also has an agronomic meaning of crop yield per unit of water use (Howell, 2001) and satellite data have demonstrated use in monitoring water use (Anderson et al., 2012). Given that satellite data stretch back to 1972 with Earth Resource Technology Satellite-1 (Landsat 1), there is huge potential for tracking how water use has changed and will continue to change over time.

Meanwhile, in the case of indicator 2.4.1, EO-based information is explicitly identified as an “alternative data source” for a variety of its sub-indicators, including farm output value per hectare (e.g. via crop mapping and area estimation), prevalence of soil degradation, variation in water availability, management of fertilizers, and use of biodiversity-supportive practices (e.g. tillage mapping, cover crop monitoring, and crop residue monitoring). It is listed as alternative, and not a primary data source, because of the concerns of high costs associated with satellite EO implementation. This highlights a particular challenge related to communication and methods/information transition between communities, which will be further discussed in Section 4. This clear potential for satellite data merits increased interaction between the UN FAO as Custodian Agency and those in the GEOGLAM community who have fostered close relationships or who themselves are working within the national agencies concerned with agricultural monitoring, state, and change.

3. EO usage for multiple policy drivers: finding the intersection

In addition to the 17 Goals, 169 targets, and 230 indicators, there are over seven hundred multi-lateral environment agreements, and many more addressing social and economic development, all with their attendant monitoring schemes and associated data requirements (Reyers et al., 2017). The emphasis on “data” is so absolute that some have argued that sourcing, quality, and governmental ownership of data production is an afterthought (Scott and Rajabifard, 2017), creating a considerable burden on producers and users alike of information about global sustainable development. Achieving the SDGs will hinge upon both identifying and leveraging complementary and overlapping activities (Pradhan et al., 2017). The IAEG-SDGs acknowledges that any global reporting on SDGs should build upon existing reporting mechanisms and focus on creating “efficient, accurate, and transparent mechanisms for reporting data to the national to international level” (IAEG-SDGs, 2018e, p. 1). In fact, nearly all of data referenced in Table 2 and 3 are broadly valuable and applicable for other agricultural and land use monitoring applications, including the 2011 G20 Action Plan on Food Price Volatility and Markets (as exemplified in GEOGLAM's core product requirements, Table 1), COP21 Paris Agreement, the REDD + mechanism, and the Sendai Framework for Disaster Risk Reduction.

A significant portion of the Paris Climate Agreement goals, which emerged from COP21 in 2016, hinges on articulated land tenure and land management regimes, which in turn rely on EO data to determine land use status and calculate carbon sequestered in a given area (Kumar and Ghose, 2017). EO can provide critical information of agricultural land use state and change in response to a changing climate, for example as it already has been by Canada to track northward expansion of long season crops like soybean in to northern parts of the Canadian prairies (Government of Canada, 2016). With respect to the Sendai Framework on Disaster Risk Reduction, EO-based agricultural monitoring supports two of the four priorities, including: Priority 1. Understanding disaster risk, and Priority 4. Enhancing disaster preparedness for effective response. In terms of risk assessment, EO-based agricultural monitoring can identify the potential impact of weather-related disasters such as drought, typhoons, and hurricanes on food production. In terms of response, EO can provide timely information on the extent and severity of events on food production that can inform emergency food response to offset losses, and inform response programs like crop insurance and other ad hoc policy measures to mitigate damage (Coutu et al., 2017).

Importantly, capacity developed to utilize EO in one domain can be leveraged for another. On 11 October 2018, landslides in Bududa, Uganda killed at least 51, displaced 858, and impacted over 12,000 people, with severe damages to crops and livestock (Assessment Capabilities Project and Start Network, 2018). With forecasts of continued heavy rains and threats of further flooding and landslides, the group within the Office of the Prime Minister Uganda responsible for reporting routinely on crop conditions and for issuing its U-NIEWS (Official Government of Uganda Inter-Ministerial/Agencies Monthly National Integrated Multi-Hazard Early Warning) Bulletin implicitly recognized the value that EO could have in this emergency context. EO data could not only aid in disaster response (e.g. identifying structures destroyed and areas to search), but also to mitigate future disasters by evaluating areas at high risk and issuing site-specific evacuations (Office of the Prime Minister Uganda - Department of Disaster Preparedness and Management, 2018).

In this complex setting of interdisciplinary, multi-scalar problems and of overlapping and complementary national, bilateral, global policy frameworks, "win-win-win" opportunities are essential, a sentiment echoed by the UN in its final report on the MDGs (United Nations, 2015b). Therefore, the creation of each novel dataset (EO-based or otherwise) should be accounted for so as to reduce duplication of effort and maximize return on investment for each indicator and its sub-components and for each national reporting mandate and its constituent efforts. Consequently, we must find a way to simplify the complexity in order to be able to begin to tackle the challenge.

3.1. Paving the way: Essential Agricultural Variables for GEOGLAM

Complex systems theory provides some insights that may help confront this issue of a proliferation of reporting responsibilities across overlapping and intersecting themes. Using this approach, a focused set of independent constraining variables can be defined based on the energy and matter requirements of the system. Dependent variables can be tracked to understand state and change in the system, and EO data are ideally suited to this task. These are known as, "Essential Variables," and as applied to our agricultural monitoring activities, Essential Agricultural Variables (EAVs) for GEOGLAM. Because they are fundamental indicators of state and change in our domain, they can be used for monitoring multiple policy dimensions. At the same time, other domains (e.g. climate, water, oceans, biodiversity) have also been exploring the concept of essential variables (Bojinski et al., 2014, 2014; Pereira et al., 2013; Pettorelli et al., 2016). The understanding and solutions to our complex global problems require an integrated approach that brings together essential variables across multiple domains. It can be argued that programs like the SDGs are coordination exercises to bring the EVs together to measure change and solve problems.

The GEOGLAM community has recognized the clear value of various national and global contributions to the SDGs and has sought a manner to clarify its value proposition and potential contribution, with the understanding being that the SDG pace is moving quickly and data/methodologies need to be presented in the simplest manner for evaluation and piloting by the member states together with the Custodian Agency, for feedback on ascending tiers, and for eventual adoption by NSOs responsible for implementing their own reporting systems. GEOGLAM has recently undertaken efforts to articulate "holistic" requirements, meaning those which track the life cycle of satellite data from acquisition through preprocessing, access, analysis, to their "conversion" into actionable information through the infusion of ancillary data and expert opinion, and onto sustained decisions (Whitcraft et al., 2018a, Fig. 1). The effort asked data producers and information users alike from the GEOGLAM community to identify top priority variables and target products for monitoring (Table 1). These included cropland and rangeland masks, crop type map and planted area, cropland and rangeland condition, crop yield forecast, water use and productivity, field delineation, crop phenology/stage, crop biophysical variables, and environmental variables. GEOGLAM's Thematic Coordination Team on Earth Observations Data Coordination and Management has launched a sub-working group on EAVs for GEOGLAM, which is tasked with defining these EAVs and their resolution, latency, precision, and accuracy requirements. This should be done in concert with those fully engaged in the UN SDG process, for example those within Custodian Agencies of selected indicators – to, a) reach consensus on the EAVs defined, b) reach consensus on the required resolutions, latency, and frequency, and c) articulate additional EAVs that have a clear policy link (or multiple links). It is worth noting that realizing the implementation of EAVs is contingent upon three key factors, and their adoption in the 2030 Agenda context upon a fourth:

1. Interaction with the operational research and development community – namely the Joint Experiment for Crop Assessment and Monitoring (JECAM), GEOGLAM's operational research and development agricultural site network – to ensure the state of science is clearly articulated to ease transformation of these data into actionable information;order
2. Coordination of satellite data assets with the world's space agencies, through the Committee on Earth Observation Satellites, to ensure the provision of the satellite data necessary to derive these variables, in accordance with Table 2 and 3;order
3. Coordination of *in situ* data necessary for calibration and validation of methodologies, a key priority for GEOGLAM and space agencies alike, one not without its challenges but well beyond the scope of this paper; and,order
4. Communication with the IAEG-SDGs, the Custodian Agencies, and member countries (i.e. NSOs and their associated agencies) to transition these methods and data into operational use. The GEOGLAM Secretariat and its community at large can assist in this communication and transition, including the development of guidelines and best practices for assisting adoption by non-EO communities.order

4. Integrating lessons learned decades of global development policies

Previous development metrics and indicators have been criticized as either too theoretical, therefore incapable of being operationalized, or of being too methodologically strict, leading to an underdevelopment of the indicators' relevance to the target on which they aim to report (Bebbington, 2004; Hák et al., 2016). The IAEG-SDGs is composed of representatives from 28 NSOs only, effectively placing EO on the periphery and in a response role, at best (Anderson et al., 2017). This is the result of siloed communities and persistent perceptions that EO are too expensive, too complex, or unreliable (due to lack of data continuity or access). In the case of indicator 2.4.1., for example, early NSO feedback on the methodology acknowledged that one of the best sources of data for one of the sub-indicators was satellite EO, but stated the high budget associated with implementation made it an unlikely possibility for national implementation (UN FAO, 2018). This is a lingering misconception of the current state of satellite datasets at a time when many EO datasets are freely and openly available with increasing interoperability, ranging from ESA Sentinel missions to NASA MODIS and NASA/USGS Landsat (Belward and Skøien, 2015; Claverie et al., 2018; Wulder et al., 2015), when computational power is becoming ever-more-available (Azzari and Lobell, 2017; Giuliani et al., 2017; Nativi et al., 2015), and when capacity development activities to support national adoption are proliferating (Desconnets et al., 2017; Hossain et al., 2016). Paradoxically, these NSOs are opting instead to use surveys, which are comparably costly (relative to area sampled), subjective, and not-easily-replicable.

There is a need for open communication between statistical and EO communities, and GEO's EO4SDG initiative has begun to approach this "translation" effort in a systematic way (Anderson et al., 2017; Kavvada and Held, 2018). Further, GEOGLAM is working with AMIS on enhancing communication between remote sensing actors and groups and national agricultural statistics groups (including several NSOs) toward facilitating cross-community collaboration and improved estimations of crop production from national to global scales. This interaction

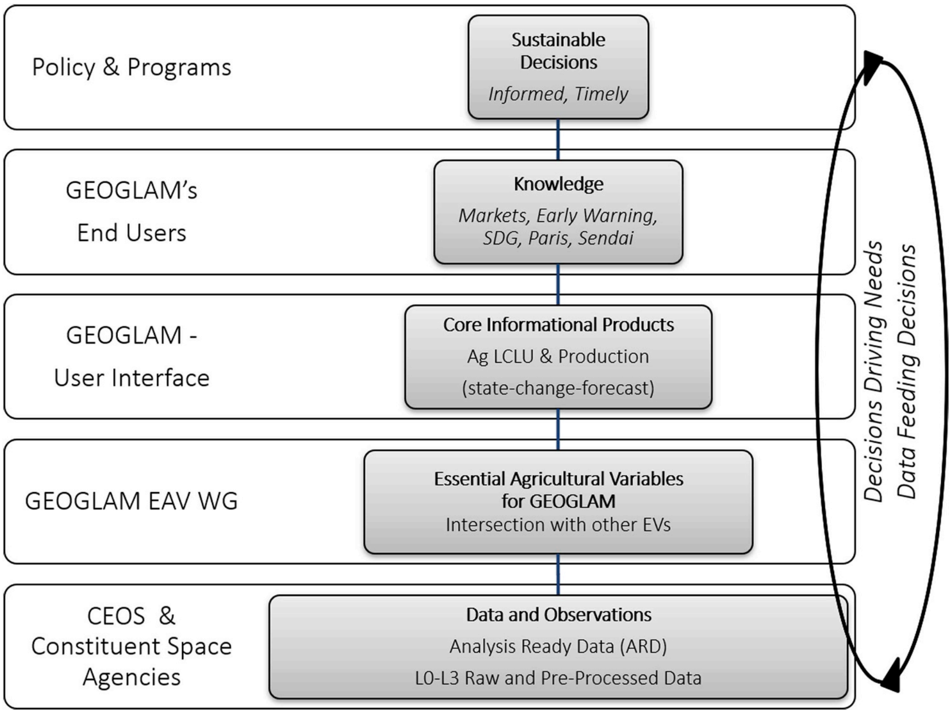

Fig. 1. The "Data to Decisions" Cycle for GEOGLAM, which is guiding the work of GEOGLAM in general and the GEOGLAM EAV working group in particular. The decision support needs drive the information and data required, and the data is processed and converted gradually into the knowledge that supports sustained decisions. At left, the primary actors for each stage in the cycle are identified, however, all steps are integrated and connected. In this schematic, the UN SDGs are among "GEOGLAM's End Users" and also occupy the "Policy and Programs" role, while the NSOs and the IAEG-SDGs in particular are proposed to be included in the discussions that also drive information products and EAVs for GEOGLAM.

provides better access by all to improved market information, including grain stocks and food reserves that are critical to understanding medium- and longer-term supply outlooks. Beyond communication, there is also the need for targeted approaches to reducing barriers to EO adoption, as satellite images in and of themselves are not solutions but rather arrays of numbers in need of analysis to derive meaningful and actionable information. These approaches include capacity development for production and interpretation of EO data and EO-derived information, documenting and promoting "good practices" for EO-usage (for example through community-generated compendiums and methodological documentation, e.g. Defourny et al. (2019); Gascon (2018); Robertson et al. (2018)), and producing consistently-validated, higher-level, "analysis-ready" products such as the EAVs for GEOGLAM, targeted at EO-expert and non-EO expert audiences alike. Each of these activities are components of GEOGLAM's 2020–2022 Work Plan (GEOGLAM Executive Committee, 2019).

As we have demonstrated in this paper, it is not necessary to start from scratch scientifically for achieving the Goals and targets, nor for measuring progress toward their achievement via indicators. Similarly, we have considerable political and operational heritage from which we can draw in order to assist with implementing EO data in the SDG context. The examples involving the Office of the Prime Minister Uganda (Office of the Prime Minister Uganda - Department of Disaster Preparedness and Management, 2018; Owor, 2018) elucidate the value of engaging national stakeholders from the beginning in order to co-design a tailored solution that results in lasting, sustained national ownership. In a global example, the GEOGLAM Crop Monitor for AMIS (CM4AMIS) represents a successful case of overcoming communication barriers between siloed groups. When the CM4AMIS was first produced, the response from the economics community to geospatial information was tentative but interested. Through iterative dialogue and consistent, respectful, inter-personal engagement, the GEOGLAM community was able to first understand AMIS agricultural economists' needs, and then deliver a product that was readily comprehensible, relevant, and above all useful to the economics community. This relationship continues to grow and evolve to meet evolving information user needs, with the November 2018 edition of the AMIS Market Monitor calling for improved methods for quantitative estimation methodologies, particularly in smallholder systems (Agricultural Market Information System, 2018). In the end, the largest value added is through the integration of EO data and derived information with that of the economics community. Similar benefits can and should be realized through combining the knowledge and resources of the statistical community with those of the EO community.

5. Conclusion

GEOGLAM has clearly articulated its satellite data requirements for deriving agricultural indicators that have broad applicability across multiple policy frameworks. There is considerable technical potential for GEOGLAM's activities and EO data at-large to contribute to the SDGs, but the need for increased community integration and solution co-design cannot be overstated. There is much to be learned – for better or for worse – from other international policy mandates, including COP 21, the G20 Action Plan on Food Price Volatility and Markets, the Sendai Framework for Disaster Risk Reduction, and the Millennium Development Goals.

There remains the task of streamlining communication between these stakeholders and finding a way to manage finite resources across multiple domains. Many of the IAEG-SDGs' Indicator Metadata descriptions mention ways in which sub-indicators or components of one indicator could be of value to other indicators. This is an important start, and this type of "meta-coordination" is critical toward reducing reporting burden in a way that is conducive to even implementation of the indicator framework across resource-strapped and resource-rich nations alike (Pradhan et al., 2017). Goal 17 (Strengthen the means of implementation and revitalize the global partnership for sustainable development) implicitly acknowledges the institutional challenges to implementation, which can often outmatch the technical ones. Meanwhile, GEO as a global community actor is in a position to take stock of existing methodologies across disciplinary areas, and "connect the dots" across siloed EO actors. Through its EO4SDG effort, GEO can provide systematic awareness raising and connection with the UN on SDGs. If the EO community – facilitated by GEO in general, and in the agricultural domain, by GEOGLAM in particular – can present a cohesive package of methodologies and indicators that have high return on investment across multiple reporting purposes (e.g. via the EAVs for GEOGLAM), this will only strengthen the position of EO and empower its use in providing timely, actionable, and policy-relevant information to confront some of the world's most pressing issues.

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Appendix

Tier Classification:

Indicators ascend through "Tiers" as consensus is built around methodologies for producing the indicators, although there are concerns about transparency of transition between Tiers (Adams and Judd, 2018). Definitions for each Tier are from the IAEG-SDGs Website (IAEG-SDGs, 2018f):

- Tier III: No internationally established methodology or standards are yet available for the indicator, but methodology/standards are being (or will be) developed or tested.bullet
- Tier II: Indicator is conceptually clear, has an internationally established methodology and standards are available, but data are not regularly produced by countries.bullet
- Tier I: Indicator is conceptually clear, has an internationally established methodology and standards are available, and data are regularly produced by countries for at least 50 per cent of countries and of the population in every region where the indicator is relevant.bullet

For an indicator to be reclassified from Tier III to Tier II, the following requirements need to be met and provided to the IAEG-SDGs for consideration (UN Statistics Division, 2018):

- National Statistical Systems (NSSs), and in particular, National Statistical Offices (NSOs) should be involved in indicator methodology development;bullet
- The methodology must be supported by international standards; reviewed, and approved by a specialized expert group or governing body; and,bullet
- Regionally representative pilot studies must be supporting the methodology development narrative, including results originating from these pilot studies.bullet

Supporting documents as part of the tier upgrading request should include:

- A short summary of supporting activities showcasing collaboration among NSOs, national mapping agencies (NMAs), other relevant government stakeholders and custodian agencies;bullet
- Metadata, including information on sources, definitions, methods of data collection and computation, data disaggregation, limitations and sources of discrepancies, as well as references; and,bullet
- Methodology development report, including information on pilot studies.bullet

For an indicator to be reclassified to Tier I, it needs to satisfy all Tier I requirements, that is, it needs to have an internationally accepted methodology and standards, and data should be regularly produced by countries for at least 50 per cent of countries, and of the population in every region, where the indicator is relevant. Therefore, it is critical that there be engagement between the NSOs and NMAs (or other geospatial entities, such as those comprising GEOGLAM), and that this engagement happen as indicators are developed, ideally while still classified as Tier III, as changes to methodologies once they have ascended Tiers becomes increasingly difficult.

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